```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import yfinance as yf
import seaborn as sns

# Download NIFTY 50 data from Yahoo Finance using yfinance
nifty = yf.download('^NSEI', start='2000-01-01', end='2024-01-01',
progress=False)

# Use the 'Close' price for predictions
df = nifty[['Close']]

# Plotting the historical closing prices
plt.figure(figsize=(14, 7))
plt.plot(df['Close'], label='Closing Price')
plt.title("NIFTY 50 Historical Closing Prices")
plt.xlabel("Date")
plt.ylabel("Closing Price (INR)")
plt.grid(True)
plt.legend()
plt.show()

# Preprocessing: Scaling the 'Close' prices
scaler = MinMaxScaler(feature_range=(0, 1))
df_scaled = scaler.fit_transform(df[['Close']])

# Splitting the data into training and testing sets (80% train, 20%
test)
train_size = int(len(df) * 0.8)
train, test = df_scaled[:train_size], df_scaled[train_size:]

# Function to create datasets for LSTM input
def create_dataset(data, time_step=1):
    X, y = [], []
    for i in range(len(data) - time_step):
        X.append(data[i:(i + time_step), 0])
        y.append(data[i + time_step, 0])
    return np.array(X), np.array(y)

# Creating dataset for LSTM (Using 30 days to predict next day's
closing price)
time_step = 30
X_train, y_train = create_dataset(train, time_step)
X_test, y_test = create_dataset(test, time_step)
```

```python
# Reshaping data to 3D format for LSTM [samples, time_steps, features]
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

# Build the LSTM model
model = Sequential()
model.add(LSTM(100, return_sequences=True,
input_shape=(X_train.shape[1], 1)))
model.add(Dropout(0.2))
model.add(LSTM(100, return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
history = model.fit(X_train, y_train, epochs=1, batch_size=32,
validation_data=(X_test, y_test), verbose=1)

# Plotting training and validation loss
plt.figure(figsize=(14, 7))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title("Training vs Validation Loss")
plt.xlabel("Epochs ")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()

# Predictions on the training and test sets
train_predict = model.predict(X_train)
test_predict = model.predict(X_test)

# Inverse scaling of predictions to original scale
train_predict = scaler.inverse_transform(train_predict)
test_predict = scaler.inverse_transform(test_predict)
y_train_actual = scaler.inverse_transform([y_train])
y_test_actual = scaler.inverse_transform([y_test])

# Adjusting the index to match the time_step offset
train_index = df.index[time_step:train_size]
test_index = df.index[train_size + time_step:]

# Fixing the length mismatch issue
train_predict = train_predict[:len(train_index)]
test_predict = test_predict[:len(test_index)]
```

```
# Plotting predictions vs actual values for the test dataset
plt.figure(figsize=(14, 7))
plt.plot(train_index, y_train_actual[0], label='Actual Train Data')
plt.plot(test_index, y_test_actual[0], label='Actual Test Data')
plt.plot(test_index, test_predict, label='Predicted Test Data',
linestyle='dashed')
plt.title("Predictions vs Actual Stock Prices")
plt.xlabel("Date")
plt.ylabel("Stock Price (INR)")
plt.legend()
plt.grid(True)
plt.show()

# Residuals (Prediction errors)
residuals = test_predict - y_test_actual[0]
plt.figure(figsize=(14, 7))
plt.plot(test_index, residuals, label='Residuals', color='purple')
plt.title("Residuals of Predictions (Predicted - Actual)")
plt.xlabel("Date")
plt.ylabel("Residuals")
plt.grid(True)
plt.show()

# Performance Metrics: MAE, RMSE, R²
mae = mean_absolute_error(y_test_actual[0], test_predict)
rmse = np.sqrt(mean_squared_error(y_test_actual[0], test_predict))
r2 = r2_score(y_test_actual[0], test_predict)

# Displaying the performance metrics
print(f"MAE (Mean Absolute Error): {mae}")
print(f"RMSE (Root Mean Squared Error): {rmse}")
print(f"R² (Coefficient of Determination): {r2}")

# Visualizing predicted vs actual stock prices (Multiple views)
plt.figure(figsize=(14, 7))
plt.plot(train_index, y_train_actual[0], label='Train Actual Data',
color='green')
plt.plot(test_index, y_test_actual[0], label='Test Actual Data',
color='blue')
plt.plot(test_index, test_predict, label='Predicted Data',
linestyle='dashed', color='red')
plt.title("Actual vs Predicted Stock Prices")
plt.xlabel("Date")
plt.ylabel("Stock Price (INR)")
plt.legend()
plt.grid(True)
plt.show()

# Visualizing the error distribution of predictions
plt.figure(figsize=(14, 7))
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sns.histplot(residuals, kde=True, color='red', bins=50)
plt.title("Distribution of Prediction Errors (Residuals)")
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.show()

# Adjust the indices to match the predictions
train_df = pd.DataFrame(train[time_step:], columns=["Scaled_Close"])
test_df = pd.DataFrame(test[time_step:], columns=["Scaled_Close"])

# Add predictions to DataFrame
train_df["Prediction"] = train_predict[: len(train_df)]
test_df["Prediction"] = test_predict[: len(test_df)]

corr_train = train_df.corr()
corr_test = test_df.corr()

plt.figure(figsize=(14, 7))
sns.heatmap(corr_train, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix - Training Data")
plt.show()

plt.figure(figsize=(14, 7))
sns.heatmap(corr_test, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix - Test Data")
plt.show()

# Comparison of predicted vs actual price difference
plt.figure(figsize=(14, 7))
plt.plot(test_index, y_test_actual[0] - test_predict,
label="Difference (Actual - Predicted)", color='orange')
plt.title("Price Difference Between Actual and Predicted")
plt.xlabel("Date")
plt.ylabel("Price Difference (INR)")
plt.legend()
plt.grid(True)
plt.show()
```
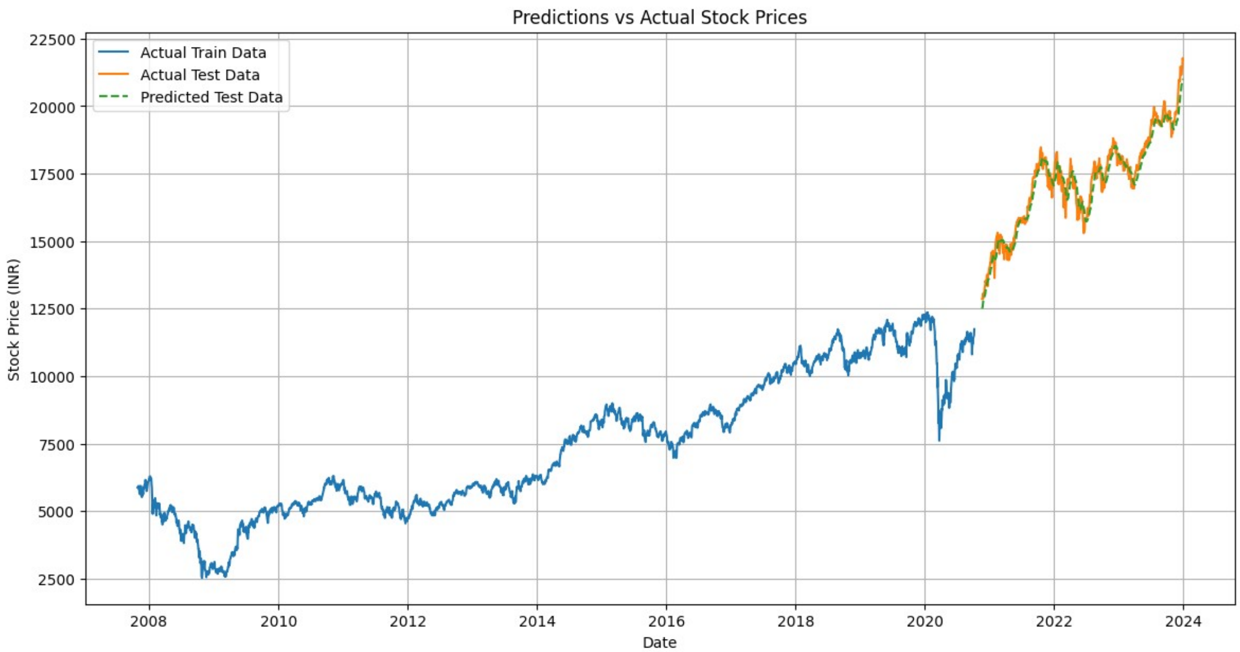
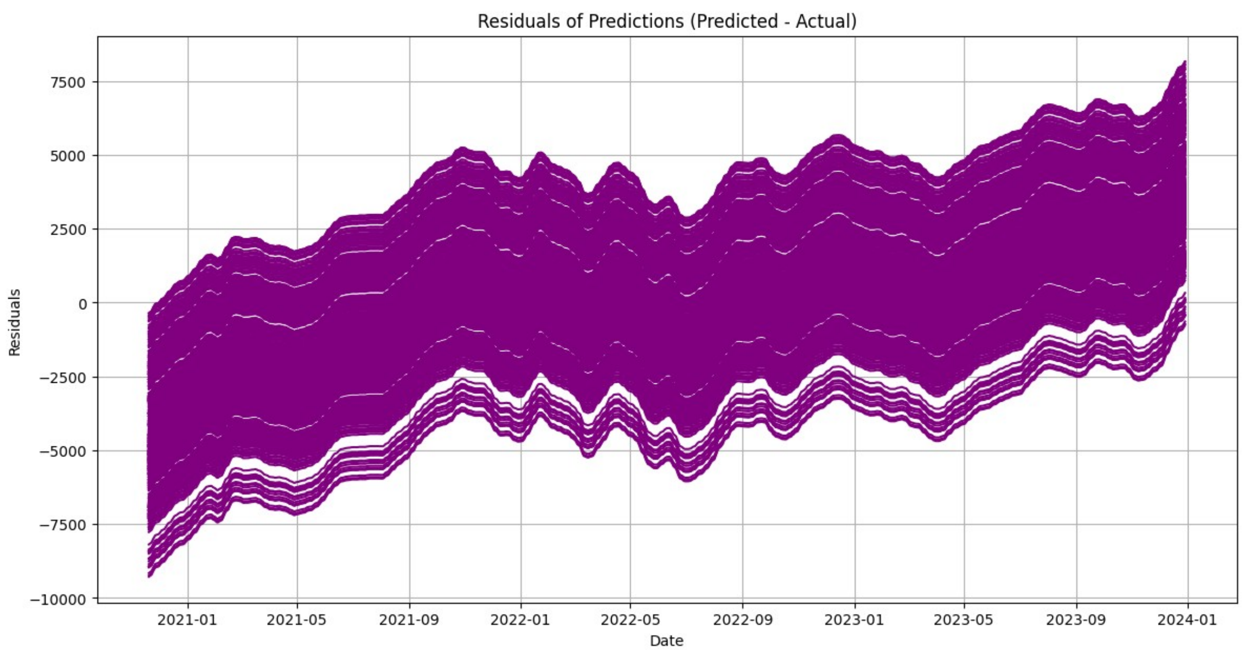


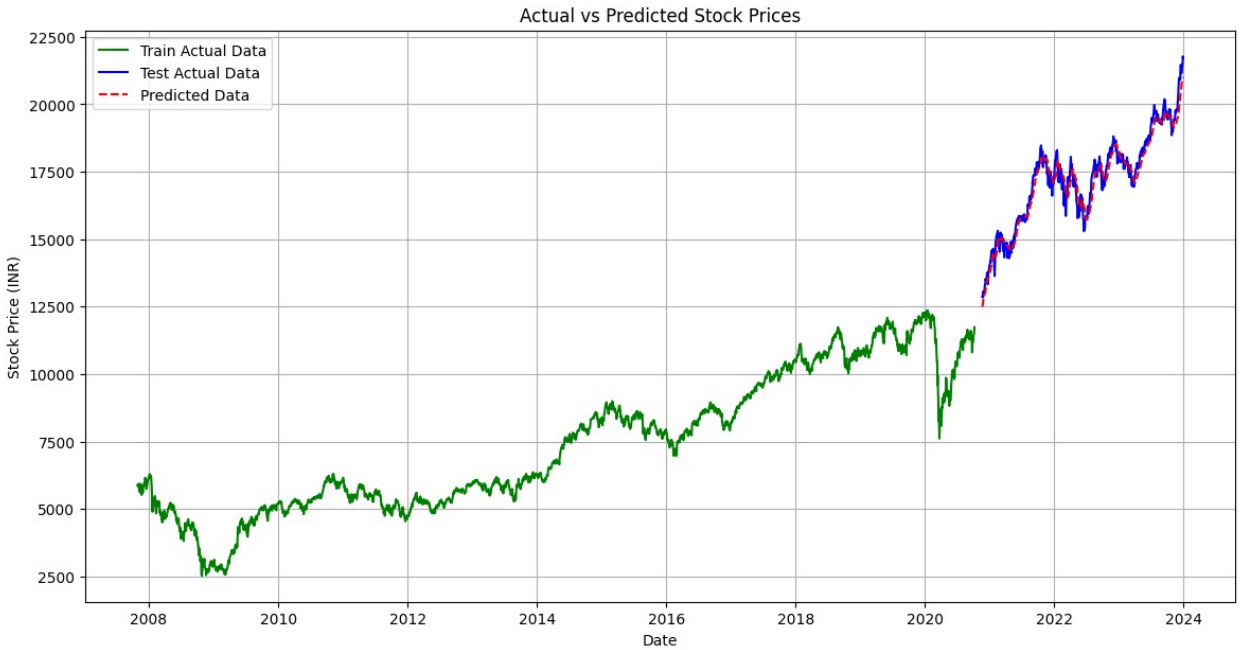
```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/
rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

99/99 ━━━━━━━━━━━━━━━━━━━━ 9s 55ms/step - loss: 0.0098 - val_loss:
3.8060e-04
```

```
99/99 ━━━━━━━━━━━━━━━━━━━━ 2s 19ms/step
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step
```

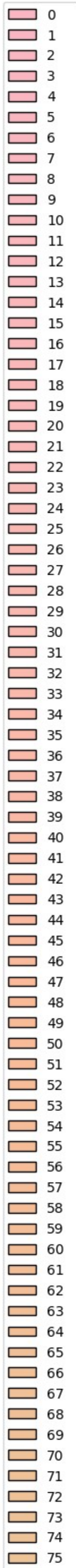





```
MAE (Mean Absolute Error): 299.9696097305754
RMSE (Root Mean Squared Error): 375.6361298135698
R² (Coefficient of Determination): 0.9534858887719505
```




```
/usr/local/lib/python3.10/dist-packages/IPython/core/
pylabtools.py:151: UserWarning: Creating legend with loc="best" can be
slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```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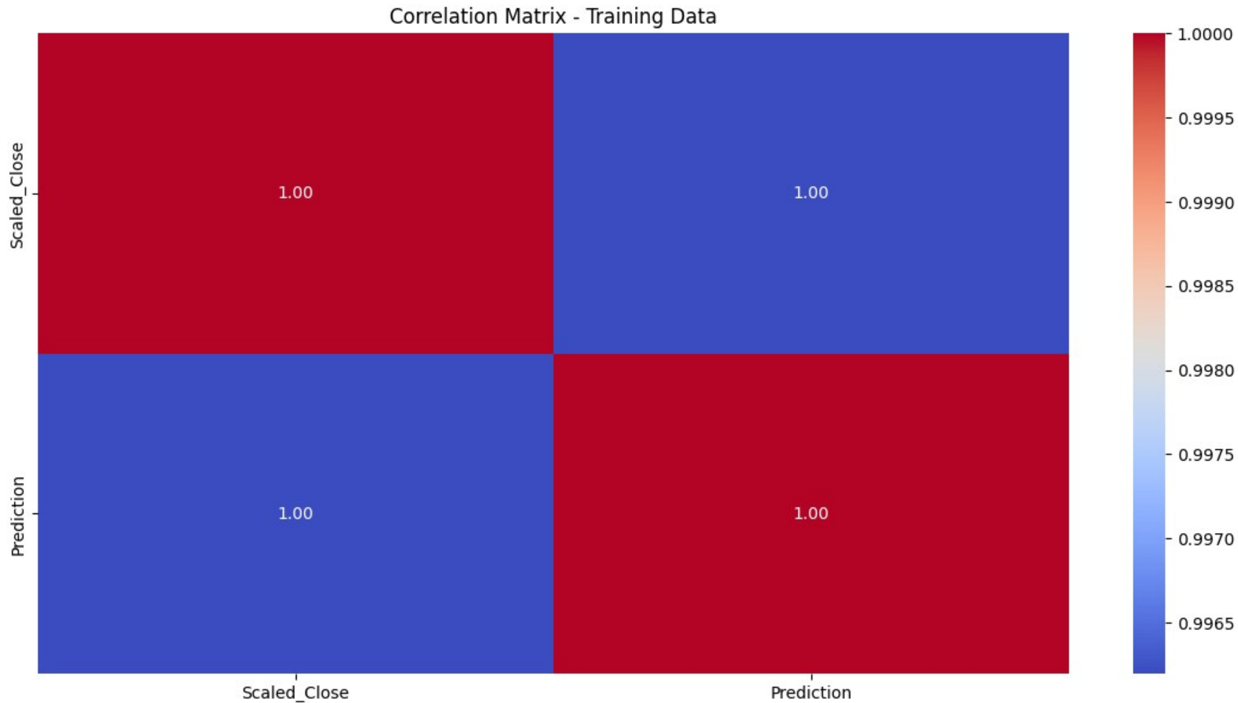
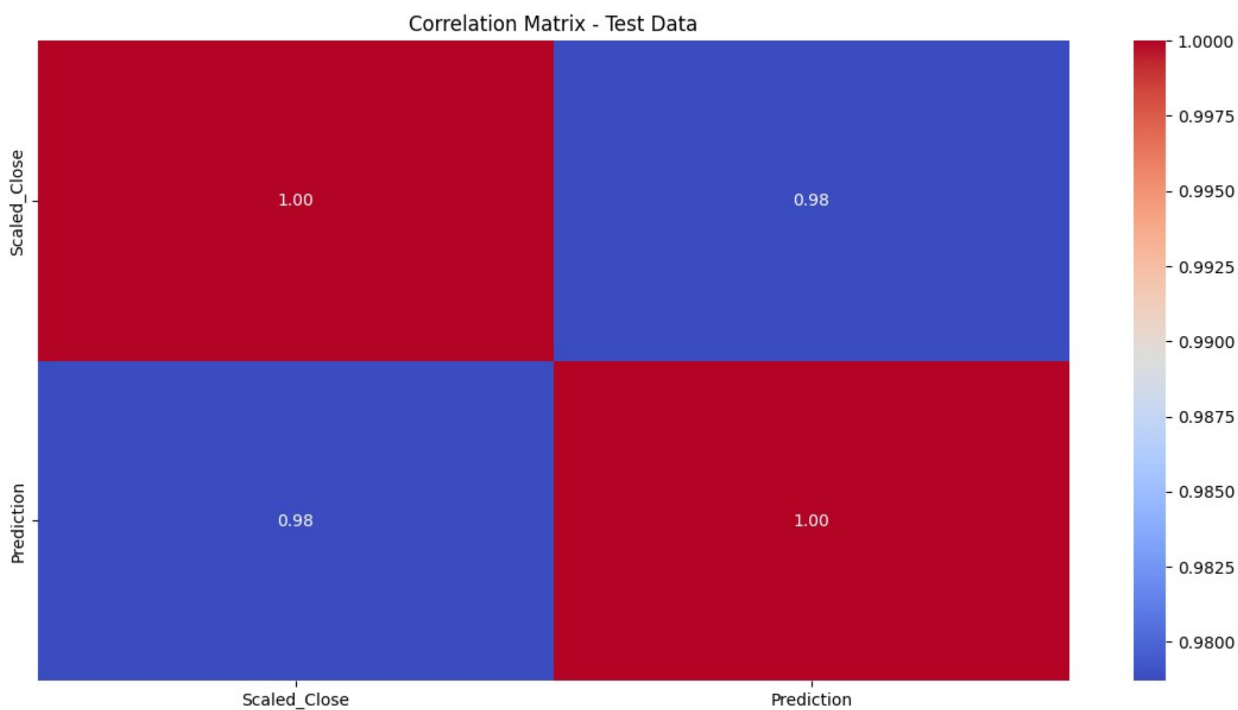
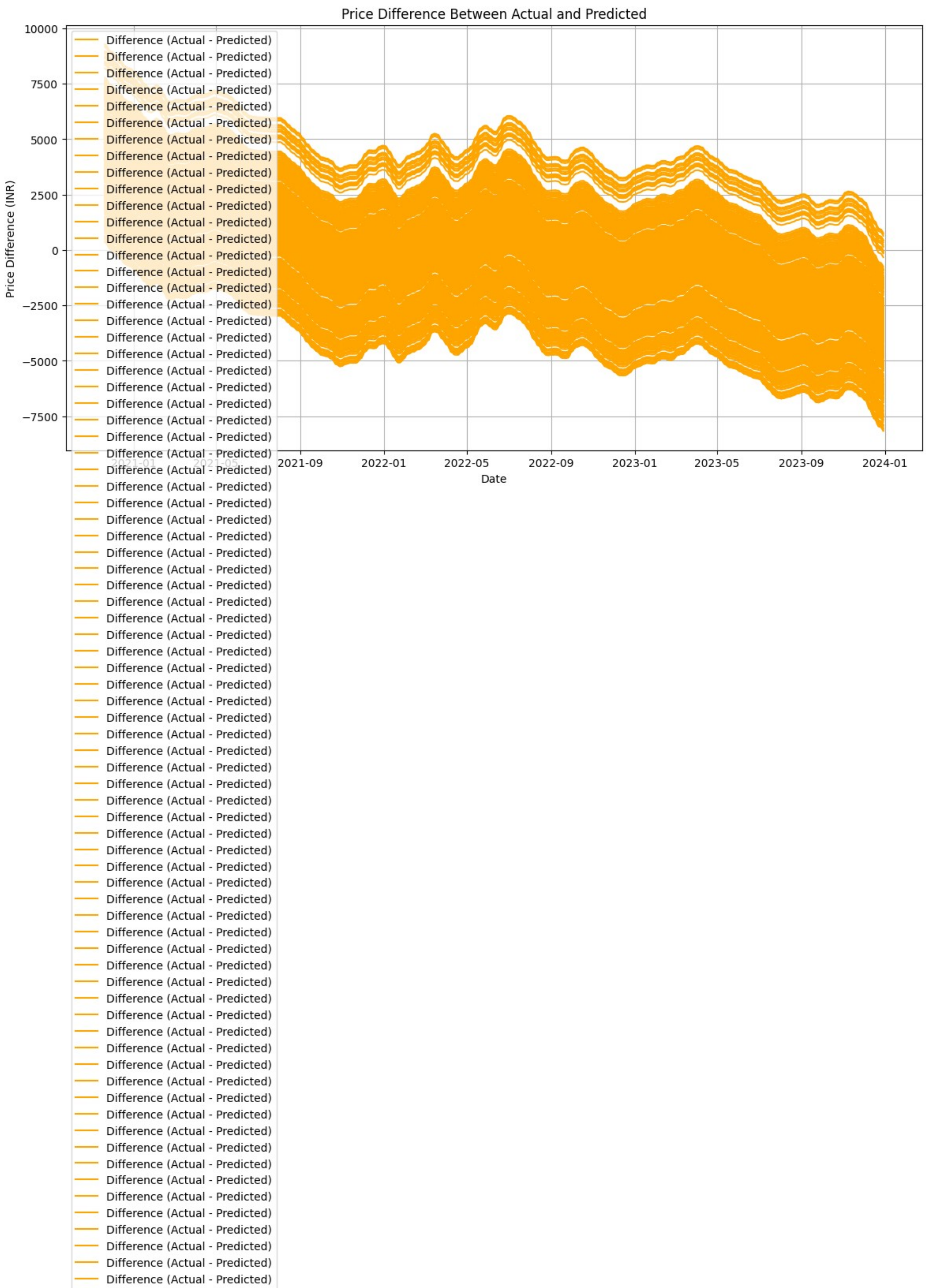

Correlation Matrix - Training Data
Scaled_Close
Prediction
1.00
1.00
1.00
1.00
Scaled_Close
Prediction
1.0000
0.9995
0.9990
0.9985
0.9980
0.9975
0.9970
0.9965


Correlation Matrix - Test Data
Scaled_Close
Prediction
1.00
0.98
0.98
1.00
Scaled_Close
Prediction
1.0000
0.9975
0.9950
0.9925
0.9900
0.9875
0.9850
0.9825
0.9800


Price Difference Between Actual and Predicted
Difference (Actual - Predicted)
Price Difference (INR)
10000
7500
5000
2500
0
−2500
−5000
−7500
Date
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01

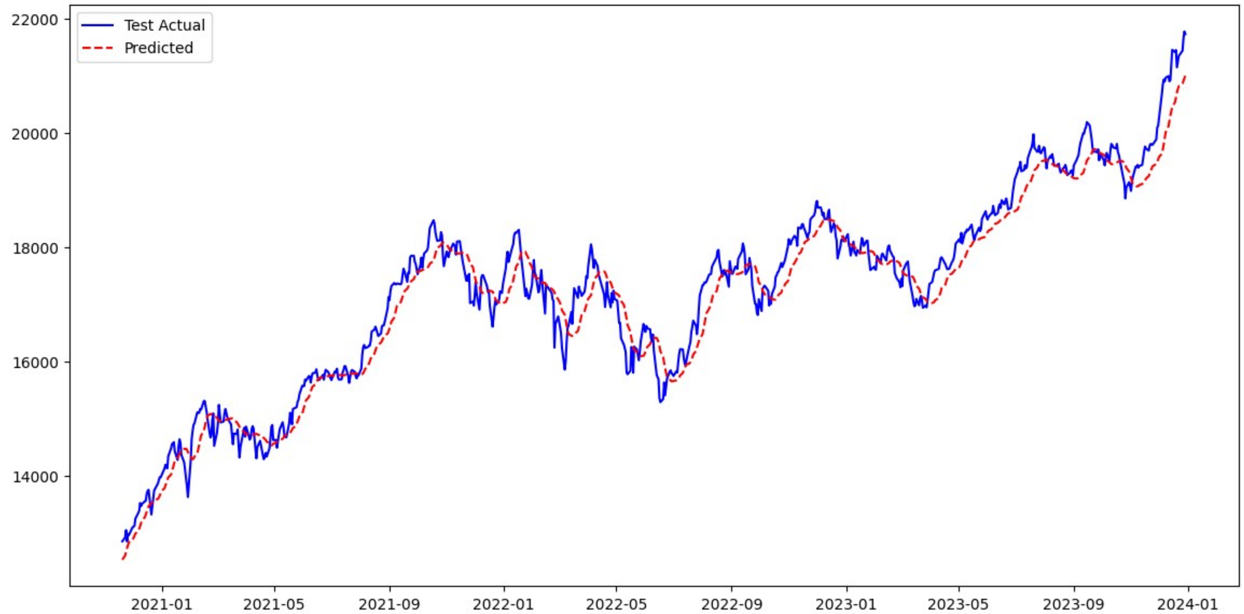
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import yfinance as yf
import seaborn as sns

# Download NIFTY 50 data
nifty = yf.download('^NSEI', start='2000-01-01', end='2024-01-01',
progress=False)
df = nifty[['Close']]

# Scaling
scaler = MinMaxScaler()
df_scaled = scaler.fit_transform(df)

# Train-test split
train_size = int(len(df) * 0.8)
train, test = df_scaled[:train_size], df_scaled[train_size:]

# Create dataset
def create_dataset(data, time_step=1):
    X, y = [], []
    for i in range(len(data) - time_step):
        X.append(data[i:i+time_step, 0])
        y.append(data[i+time_step, 0])
    return np.array(X), np.array(y)

time_step = 30
X_train, y_train = create_dataset(train, time_step)
X_test, y_test = create_dataset(test, time_step)
X_train = X_train.reshape(-1, time_step, 1)
X_test = X_test.reshape(-1, time_step, 1)

# Model
model = Sequential([
    LSTM(100, return_sequences=True, input_shape=(time_step, 1)),
    Dropout(0.2),
    LSTM(100),
    Dropout(0.2),
    Dense(1)
])
model.compile(optimizer='adam', loss='mean_squared_error')
history = model.fit(X_train, y_train, epochs=2, batch_size=32,
validation_data=(X_test, y_test))
```

```python
# Predictions
train_predict = scaler.inverse_transform(model.predict(X_train))
test_predict = scaler.inverse_transform(model.predict(X_test))
y_train_actual = scaler.inverse_transform([y_train])
y_test_actual = scaler.inverse_transform([y_test])

# Indices
train_index = df.index[:len(train_predict)]
test_index = df.index[len(df) - len(test_predict):]

# Visualization
plt.figure(figsize=(14, 7))
plt.plot(test_index, y_test_actual[0][:len(test_predict)], label='Test
Actual', color='blue')
plt.plot(test_index, test_predict.flatten(), label='Predicted',
linestyle='dashed', color='red')
plt.legend()
plt.show()
```

```
Epoch 1/2
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/
rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
99/99 ━━━━━━━━━━━━━━━━━━━━ 9s 57ms/step - loss: 0.0134 - val_loss:
4.0917e-04
Epoch 2/2
99/99 ━━━━━━━━━━━━━━━━━━━━ 6s 60ms/step - loss: 5.3951e-04 - val_loss:
3.7134e-04
99/99 ━━━━━━━━━━━━━━━━━━━━ 2s 21ms/step
25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step
```


Test Actual
Predicted
22000
20000
18000
16000
14000
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01